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A simulation model shows how individual differences affect major life decisions

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ABSTRACT Individuals are faced with a number of major decisions throughout their lives, including the choice of a suitable education, career, and life partner. Making such major life decisions is challenging, as is evidenced by substantial rates of divorce and drop-out from higher education. Although poor major life decisions can lead to considerable costs for both individuals and society, little is known about how people make these decisions. This is because major life decisions are not simple short-term weighings of options—they are strongly intertwined with identity development. Here, we present a simulation model of major life decisions that integrates the short-term perspective of decision science with the long-term perspective of identity theory. We model major life decisions as a process comprising many explorations of available options, resulting in changing commitments, and eventually leading to a decision. Using our model, we run a large-scale in silico experiment, systematically simulating how three key individual characteristics affect the choice process and the quality of the decision: (1) exploration tendency (broad vs. in-depth), (2) accuracy in assessing how well options fit, and (3) selectiveness. We identify the types of individuals who are at risk of exhibiting 'maladaptive' decision dynamics, including ruminative exploration and rash decision making, and conclude that these features often, but not always, lead to bad decisions. Our simulation results generate concrete predictions that can be empirically tested and may eventually result in individually tailored tools to aid individuals in making major life decisions.

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Introduction

Starting in adolescence, when individuals are first faced with choosing a career path, individuals make various major life decisions: high-impact decisions that typically involve a large number of options to choose from, with an uncertain outcome. Because the outcomes of pursuing the various available options tend to be difficult to estimate in advance, making a major life decision is not easy. This is evidenced by the relatively high frequency that they turn out to be suboptimal, sometimes with considerable negative consequences. Of course, making a 'wrong' decision does not always have to turn out negatively—it can be a chance for personal growth as well—but the risks of negative outcomes are real. For example, many young individuals, having chosen an education programme out of hundreds or even thousands of options, end up dropping out of tertiary education. These dropout rates range from about one in five (Denmark) to more than half (Italy; Quinn, 2013). This can set into motion a series of events that put the individual at risk of becoming 'NEET' (Not in Employment, Education or Training; Siraj et al. 2014; European Training Foundation, 2014) which is associated with poor physical and mental health 20 years later (Feng et al., 2018) and long-term employment instability that also carries societal costs (Côte, 2015). Another example is the high rate of divorce that is observed globally, which can also come at significantly negative consequences for the involved individuals (Amato, 2000). Indeed, in western societies, decisions in the domain of education are generally regretted the most, followed by decisions in the domain of career, romantic partners, parenting, self-improvement, and leisure activities (Roese and Summerville, 2005).

Despite the importance of major life decisions in various domains, we still know very little about how individuals make these choices. One important reason for this lack of understanding is that major life decisions take place in the grey zone between decision making and identity development. Therefore, the disciplines that study these two phenomena, respectively, decision science (a field traditionally dominated by cognitive psychology and rational choice theories from economics) and identity science (a branch of developmental psychology), are both insufficiently equipped to help us understand how major life decisions are actually made. The aim of this paper is to achieve a better understanding of major life decisions by developing a framework that integrates these two perspectives. Because major life decisions result from long-term processes that depend on the complex interaction of various individual characteristics, we decided to develop an explicit simulation model to capture the behaviour of this process. We use our model to run a large-scale in silico experiment, generating concrete predictions of how individual characteristics affect the decision-making process and its outcome. This offers opportunities for further empirical research, and, in the longer term, may contribute to developing strategies to intervene in major life decision processes that are at risk of turning out poorly.

Theory

In decision science, decision making is traditionally viewed as a (potentially biased) weighing of costs, benefits, and risks in a single moment in time (Oppenheimer and Kelso, 2015). Although this may be a suitable conceptualisation for various types of simple decisions (which brand of toothpaste to buy, which stock to invest in), this micro-perspective is ill-fitted for studying the complex and dynamic nature of major life decisions (such as career decisions; Pryor and Bright, 2011; Rottinghaus and Van Esbroeck, 2011; Van der Gaag, 2017). Having said this, recent years have seen a growing interest in approaches that conceptualise decision making as a dynamic process (Oppenheimer and Kelso, 2015). This has resulted in models that treat decision making as a sequence of basic nonlinear cognitive and emotional processes that are under various constraints (e.g., Busemeyer and Townsend, 1993; Johnson et al., 2007), rather than assuming a 'black box' psychology that is an optimisation machine. Although these approaches are promising, they have not yet been adapted to incorporate some of the crucial elements of the long-term decision-making processes that characterise major life decisions. Most importantly, these models do not take into account that differences in individual characteristics can have a significant impact on the process of major life decision making.

The individually variable characteristics that affect long-term decision-making processes have received attention in identity science for at least 50 years. Identity theorists view making major life decisions as a process of identity development, characterised by three main aspects: an individual *explores* different options (Marcia, 1966), which results in *experiences* that inform the individual how well these options fit them (Bosma and Kunnen, 2001; Grotevant, 1987; van der Gaag et al., 2017; Vleioras and Bosma, 2005), leading the individual to adjust their *commitment* towards these options (high commitment to an option makes it likely that the individual eventually chooses it; Germeijs and Verschueren, 2007). Identity research has identified the main ways in which people differ across all three of these aspects (i.e., how individuals explore, experience and form commitments to different options). First, there are differences between individuals in whether they prefer to explore broadly, sampling many new options, or prefer to explore in-depth, mainly investigating promising options further (depending on their personality; Luyckx et al., 2006). Second, individuals differ in their information processing style: some are more consistent than others in the interpretation of their experiences relative to their notions of identity (Berzonsky, 2004), leading to differences in how accurately individuals can assess whether options fit their existing preferences and capabilities. Third, individuals vary in the degree of commitment they require before making a decision; some are very selective, only deciding when they are very committed and sure that a decision is right for them, whereas others have a lower selectiveness, making decisions more readily (Germeijs and Verschueren, 2007).

Despite these major strides in understanding how individuals vary in the way that they make major life decisions, identity science lacks the tools to illuminate how these individual differences lead to different outcomes. This makes it hard to understand the emergence of decision-making processes that have generally been considered as 'maladaptive', such as rash decision making (making decisions after too little exploration), which is associated with low levels of academic commitment and social adjustment (in case of career choice; Germeijs et al., 2012), and ruminative exploration (excessive repeated exploration of the same options; Luyckx et al., 2008), which is associated with depression and low self-esteem (Beyers and Luyckx, 2016). The lack of a clear way to predict how individual differences affect the risks of exhibiting these maladaptive features of the choice process (or indeed, of making poorly fitting decisions in general) makes it difficult to develop clear strategies for intervening in problematic decision-making process.

Method

In this paper, we systematically investigate how individual differences affect the process of major life decision making by combining the perspectives of decision science and identity science in a simulation model. The construction of a formal model is useful when considering processes that are dynamic and complex (which processes of individual development invariably are; Van Geert, 1994), especially when attempting to understand how multiple factors act in concert to shape the process (in our case, how individually variable characteristics interact to shape major life decision making). In contrast to making a verbal argument, developing a formal model requires that assumptions are stated explicitly and unambiguously, which in turn leads to a precise formulation of the supposed causal relationships in the model. This facilitates the clear-cut derivation of hypotheses from the model outcomes, ultimately helping to design succinct empirical studies that can test these hypotheses. Perhaps most importantly, cementing verbal reasoning into an explicit model helps avoid vagueness in reasoning and terminology (Courgeau et al., 2017), which can help combat the 'tower of babel' that threatens to emerge in fields like identity science (Côte, 2015). Because of these advantages, computational approaches are being increasingly used to help understand processes of individual development (Mareschal and Thomas, 2007; Shultz, 2013; Oppenheimer and Kelso, 2015).

Our model is implemented as a computer program (written in C++) that simulates individual trajectories of major life decision making based on individual characteristics (partly based on Van der Gaag and Van den Berg, 2017). It simulates the choice process as a series of many exploration events in which the individual encounters various potential options, such as potential career paths or potential romantic partners. These explorations can either be broad or in-depth, and result in experiences that over time improve the individual's assessment of how well options fit with her preferences and capabilities (in line with identity theory). Eventually, if the individual estimates that an option fits her well enough (i.e., identifies with the potential commitment), she decides for that option (i.e., makes the commitment). We use our model to run a large-scale in silico experiment, simulating billions of individual major life decision trajectories, systematically varying the individual's exploration tendency (the balance between broad and in-depth exploration), accuracy (how accurately individuals assess whether options fit their existing preferences and capabilities), and selectiveness (how readily individuals consider or choose options). This way, we get a systematic overview of how individual differences in these three core identity process variables affect the dynamics and outcomes of the choice process. Specifically, we investigate which combinations of characteristics lead individuals to choose options that fit them well, and which characteristics lead to the 'maladaptive patterns' of ruminative exploration and rash decision making. Finally, we discuss whether these maladaptive patterns are actually associated with poorly fitting decisions (this is still an open question in identity research; Dietrich et al., 2012).

Figure 1 provides a general schematic overview of our model. Any choice trajectory consists of a large number (up to 100) of exploration events that can each be either broad or in-depth. Each trajectory always starts with a broad exploration, in which the individual encounters a new option that has a certain *objective fit* (x_o) with her preferences and capabilities. The objective fit reflects the idea that if chosen, some options will turn out to fit an individual better than others, under the assumption that the individual's preferences/capabilities and the nature of the options do not change during the choice process. We made this assumption for purposes of model simplicity, but we do not wish to claim that in reality consequences of choices are completely pre-determined. In the model, this objective fit is a constant random number drawn from a normal distribution with mean 0 and standard deviation 1. With this implementation we assume that options that fit very well or very poorly are relatively rare, whereas options that have an intermediate objective fit are most common. Individuals are not perfect in assessing how well an option fits their preferences and capabilities. This is because individuals are not yet fully acquainted with an option when they first encounter it (leading them to not be able to assess its fit perfectly), they may be subject to biases (e.g., the way an option is presented to them may affect their assessment of its fit), or they may simply be affected by their mood at the time they encounter an option (possibly overestimating the fit of an option when they are in a better mood). To reflect this, individuals have a *perceived fit* (x_p) that is based on the objective fit, but also contains some error (ε):

$$x_p = x_o + \varepsilon \tag{1}$$

The amount of error ε depends on the *accuracy* (α) of the individual: the more accurate the individual, the lower the error component in the perceived fit. Specifically, ε is drawn from a normal distribution with mean 0 and standard deviation σ, where $\sigma = 1 - \alpha$. In our simulations, we consider individual differences in α that range from 0 to 1, meaning that the most accurate individuals ($\alpha = 1$) can immediately perfectly assess the objective fit of a new option ($\varepsilon = 0$) whereas the least accurate individuals ($\alpha = 0$) have an error that is drawn from the same distribution as the objective fit itself ($\sigma = 1$), resulting in a perceived fit that is not very informative about the objective fit of an option. Individual differences in accuracy can be rooted in differences in information processing styles (Berzonsky, 2004) or self-concept clarity (Rottinghaus and Van Esbroeck, 2011; Crocetti et al., 2016) or in the degree to which individuals are affected by cognitive biases (Tversky and Kahneman, 1974; Stanovich and West, 2000; Teovanović et al., 2015), such as the 'halo effect' (e.g. Cook et al., 2003), which muddles the evaluation of the fit of options purely by the way in which they are presented.

Directly after exploring, the individual evaluates whether the newly explored option fits well enough with her preferences and capabilities to take it under consideration as an option to potentially choose. This evaluation depends on her *selectiveness*, implemented by her *consideration threshold* (θ_1; see Fig. 1). Specifically, if the perceived fit x_p exceeds θ_1, the individual will take the option under consideration. Otherwise, she discards the option. In our simulations, individuals can have a maximum of three options under consideration at any point in time. If the individual already has three options under consideration, the newly sampled option replaces the option under consideration that has the lowest x_p (or, if it has a lower x_p than all options currently under consideration, it is discarded). By assuming that selectiveness in choosing options is determined by aspiration levels (and time constraints; see below), we broadly follow existing cognitive information processing models, such as decision field theory (Busemeyer and Townsend, 1993; Schwartz et al., 2002), and identity theory (by incorporating a process of commitment making that is separate from identification with commitment; Luyckx et al., 2006).

As soon as an individual has any options under consideration, she may also explore in depth, further investigating previously explored options, in addition to more broad exploration to sample new options. The balance between broad and in-depth exploration is determined by the individual's *exploration tendency* (m), which is bound between 0 and 1: whenever the individual explores, she has a probability m to engage in broad exploration, and probability $1 - m$ to engage in in-depth exploration (see Fig. 1). The distinction between these two types of exploration is abundantly supported by many studies on career choice and identity development (e.g., Gati and Asher, 2001; Luyckx et al., 2006; Porfeli and Skorikov, 2010), as is the fact that individuals differ in how much they engage in either type of exploration

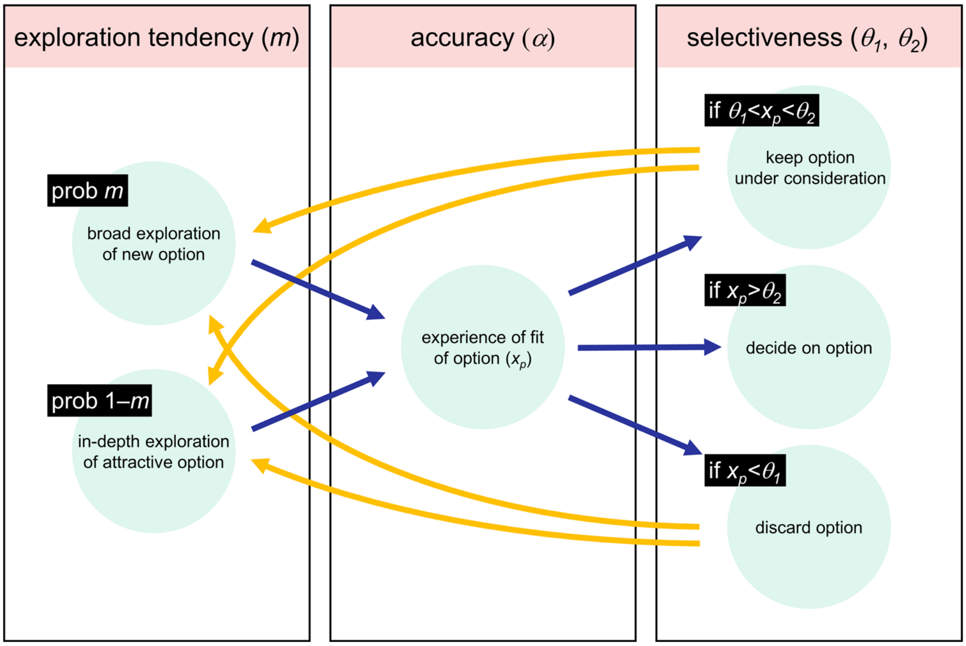

Fig. 1 The structure of the major life decisions simulation model. We model major life decisions as a process built up from many exploration events, encompassing both broad exploration (in which a new option is investigated) and in-depth exploration (in which individuals gain more experience with an option they are already considering). The individual characteristic exploration tendency (m) determines how likely an individual is to engage in either broad exploration (with probability m) or in-depth exploration (with probability 1–m) at any given point in time. Both types of exploration result in an experience with an option, which leads to a perception of how well the explored option fits with the individual's interests and capabilities (x_p). This 'perceived fit' is partly dependent on the inherent 'objective fit' of an option, but it is also affected by the individual's accuracy (α) in assessing the fit of options. If the perceived fit of a recently explored option does not meet the standards of the individual—this depends on the individual's selectiveness (specifically, the consideration threshold, θ_1)—the option is discarded from the set of options under consideration, and the individual again engages in exploration. Conversely, if the perceived fit of an option is high enough (also depending on the individual's selectiveness; the decision threshold θ_2), the individual enters the mode of final decision making, likely leading the decision making process to its end. If the objective fit of the newly explored option neither falls short of θ_1 nor exceeds θ_2, the option is kept under consideration and the individual explores again.

(Klimstra et al., 2012; Luyckx et al., 2014). If the individual engages in in-depth exploration, one of the options that are currently under consideration is selected at random, and the individual has a new experience with this option. Based on this experience, the perceived fit x_p of this option is updated. The updated perceived fit (x_p') depends on the previous perceived fit (x_p) as follows:

$$x'_p = \frac{x_p kr + x_o + \varepsilon}{kr + 1} \quad (2)$$

where k denotes the number of times the option has already been explored in the past, r represents a recency factor, determining the relative importance of past experiences ($r = 0.5$ for all simulations shown), and ε is an uncertainty component associated with the current experience, drawn from a normal distribution with mean 0 and standard deviation σ (reflecting the individual's accuracy, see above). The use of the factor k ensures that the relative impact of the current experience (represented by $x_o + \varepsilon$) on the perceived fit is lower if the option has already been explored many times before. Additionally, the use of recency factor r ensures that more recent experiences are weighed more heavily than experiences further in the past (Davelaar et al., 2005). After x_p has been updated through in-depth exploration, the individual again evaluates whether she will keep the option under consideration (depending on her selectiveness, see above).

At the end of each time step (after broad-depth or in-depth exploration has taken place), the individual determines whether the fit of the option is good enough to make her final choice for it. Again, this depends on her selectiveness, in this case implemented by her *decision threshold* (θ_2; see Fig. 1). If x_p exceeds θ_2 (and for as long as this remains the case), the individual will enter the mode of final decision making. When in this mode, at the start of each time step, the individual has a probability c (the confidence factor; for all results shown, $c = 0.5$) to make the final decision for the option exceeding θ_2. With the complementary probability (1–c), the individual will explore this option in depth. This continues until either the final decision is made (in which case the simulation ends), or in-depth exploration has caused the perceived fit (x_p) of the option to decrease to a value below θ_2, in which case the individual enters back into the regular mode of decision making. The implementation of a mode of final decision making reflects the possibility that individuals desire to accumulate more evidence to increase their confidence before making the final decision (i.e., post-decisional processing of confidence judgements as proposed in the two-stage dynamic signal detection theory; Pleskac and Busemeyer, 2010). If the choice process reaches time step 100 without having reached a decision, the individual simply chooses the option currently under consideration that has the best perceived fit. If there are no options under consideration at this point (for example, because of a very large value of θ_1), the individual chooses a randomly sampled option.

We systematically investigated the impact of individuals' exploration tendency (m), their accuracy in assessing the fit of options (α), and their selectiveness (θ_1 and θ_2) on the decision-making process. To do this, we ran a large number of simulations across a broad range of parameter combinations: 160,000 combinations of m, α, θ_1 and θ_2, and 25,000 replicate simulations for each parameter combination investigated (totalling 4 billion

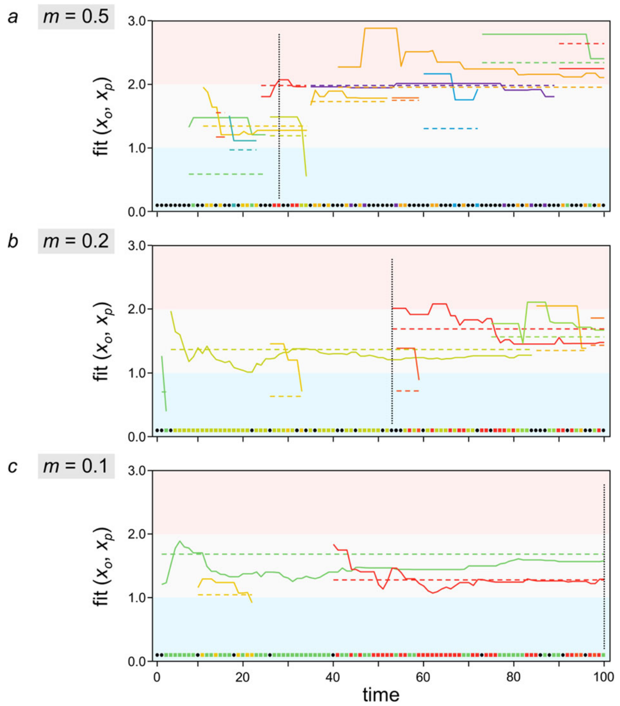

Fig. 2 The simulated decision trajectories of three different individuals a–c. The objective and perceived fit of choice options are represented by pairs of lines of matching colours. Stable, dashed lines represent the objective fit (x_o) of an option (which is always constant). The (colour-matched) fluctuating, solid lines represent the perceived fit of that same option (x_p, which changes as a result of in-depth exploration of that option). When the perceived fit of an option enters the red area ($x_p > \theta_2$) the individual enters the mode of final decision making for that option. A decision is indicated with a vertical, dotted line (for example in *a* at $t = 28$—for illustrative purposes, we have continued these simulations even when a decision was already made). An option is discarded when its perceived fit enters the blue area ($x_p < \theta_1$; for example the yellow option in *c* at $t = 22$). The symbols at the bottom of each graph indicate the event that occurred in each time step. Black circles represent broad exploration events; a new pair of coloured lines start at that time point if the newly explored option has a high enough perceived fit. Coloured squares represent events of in-depth exploration (the colour of the square indicates which option was explored in depth). The exploration tendency is different for each of the three simulated career trajectories: $m = 0.5$ **a**, $m = 0.2$ **b**, and $m = 0.1$ **c**. The other parameters are constant for these simulations (accuracy $\alpha = 0.5$, selectiveness $\theta_1 = 1.0$, $\theta_2 = 2.0$).

simulated choice trajectories; Fig. 2 shows three representative examples). Specifically, we varied m from 0.001 to 0.2 (in increments of 0.001), α between 0.0 and 1.0 (in increments of 0.005), θ_1 between 0.0 and 1.0, and θ_2 between 1.5 and 2.5. For each parameter combination, we tracked how many times individuals on average explored single options (giving us a way to assess the maladaptive choice processes of ruminative exploration and rash decision making) and recorded the average objective fit of the option that was finally chosen (allowing us to determine the quality of the choices that are eventually made).

Results

Figure 3 gives a complete overview of the outcomes of our simulations of individual major life decision-making trajectories, for a large range of combinations in individual characteristics. The figure shows how exploration tendency (m), accuracy (α) and selectiveness (consideration threshold θ_1 and decision threshold θ_2) affect the quality of the choice (Fig. 3a), the total time it takes to make a decision (i.e., degree of rash decision making; Fig. 3b), and the average time spent exploring each option under consideration (i.e., degree of rumination; Fig. 3c) in our simulations. Figure 3a reveals that the objective fit of the options chosen by the individuals in our simulations does not always follow from their individual characteristics in a straightforward manner. Generally speaking, high selectiveness (high consideration [θ_1] or decision threshold [θ_2]) tends to lead to better decisions, as does a strong tendency to explore broadly (high m), and a high degree of accuracy (high α). Conversely, the combination of low standards for deeming an option worthy of considering (low θ_1) and a tendency to explore options mostly in-depth (low m) tends to lead to decisions that yield relatively poor decisions (low objective fit). Having said that, it is not true that broad exploration is always better than in-depth exploration, that it is always good to have high standards, or even that it is best to be as accurate as possible when estimating the fit of an option. For example, our model predicts that relatively inaccurate individuals make the best choices if they explore mainly in depth, whereas relatively accurate individuals make better choices if they engage in more broad exploration (see red lines in Fig. 3a).

In our simulations, less accurate individuals tend to make their decisions more quickly than more accurate individuals (Fig. 3b). This happens because less accurate individuals perceive more variation in the fit of options, and are therefore more likely to perceive any given option as fitting either very poorly or very well. This fits with our model prediction that individuals with low accuracy make better decisions if they explore more in depth (red lines in Fig. 3a); because these individuals risk making bad choices based on an inaccurate view of the fit of the options they encounter, they are better off evaluating options more often to obtain a more accurate picture. This is especially true for individuals with a low decision threshold ($\theta_2 = 1.5$), who are most at risk of making rash decisions (i.e., coming to a decision after fewer than 20 explorations). A comparison of Fig. 3a with Fig. 3b reveals that rash decision making generally leads to relatively poor outcomes in our model. Extremely short decision times (fewer than 10 explorations) hardly occur, but when they do, the objective fit of the chosen option tends to be below the decision threshold, meaning that the individual chooses an option that they would probably not have chosen if they would have explored in depth more often. However, our simulation results also predict that quick decisions are not always bad; relatively accurate individuals ($\alpha > 0.5$) that are not very selective ($\theta_2 = 1.5$) can reach satisfactory outcomes with quick decisions.

Figure 3c shows that rumination (where individuals explore the same option at least 10 times) only occurs in our model when individuals have a strong tendency to engage in in-depth exploration ($m < 0.1$). This is particularly the case for generally selective individuals ($\theta_1 = 1.0$ and $\theta_2 = 2.5$). Like rash decision making, ruminative exploration in our simulations often leads to bad choices, but not always. Although high levels of rumination are associated with very poor decisions if individuals readily take options under consideration ($\theta_1 = 0.0$), this effect is not as clear for individuals with a high consideration threshold ($\theta_1 = 1.0$). For example, for individuals who are generally selective ($\theta_1 = 1.0$ and $\theta_2 = 2.5$) and have low accuracy ($\alpha < 0.5$), rumination hardly affects the quality of the choice that is eventually made (compare Fig. 3a, c). Figure 4 shows that simulated ruminative choice trajectories can not only have a mildly positive effect on decision quality for individuals with low accuracy ($\alpha = 0.0$), but also have the beneficial effect that it reduces the variance in the quality of the decision that is made, thereby preventing very bad choices. Specifically, our model predicts that non-ruminative decision trajectories of individuals with low accuracy have a considerable risk of resulting in choices with an objective fit below θ_1 (i.e.,

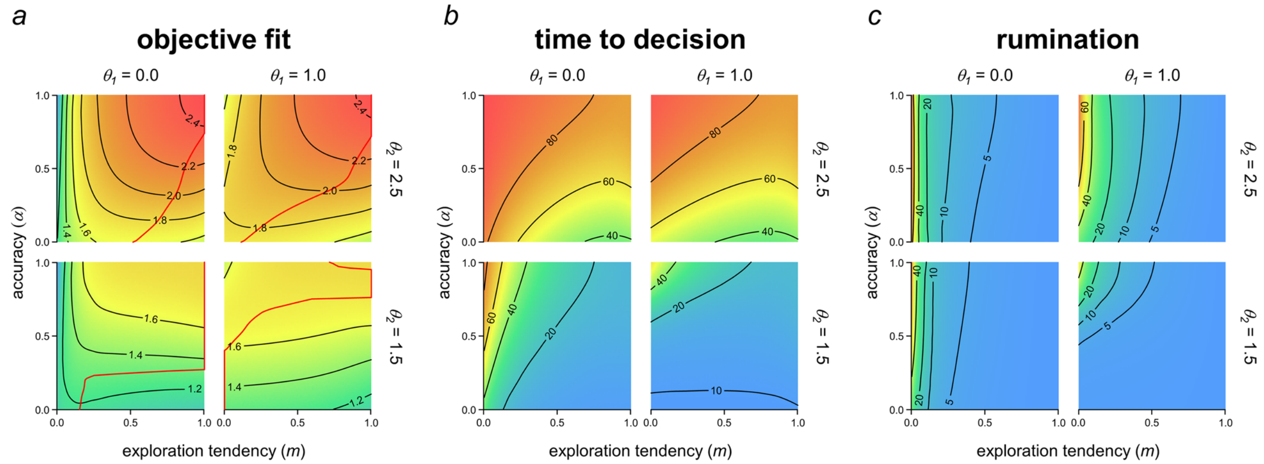

Fig. 3 An overview of (a) the objective fit of the final decision, (b) the time it takes before a decision is made and (c) the time individuals spend ruminating, depending on a broad range of parameter combinations. The four panels within each of these subplots show a combination of two consideration thresholds (θ_1) and two decision thresholds (θ_2). Within each of these four panels, the exploration tendency (m, on the x-axis) and accuracy (α, on the y-axis) vary (between 0 and 1 in steps of 0.01). In figure **a**, colours (and black contour lines) indicate the objective fit of the chosen option for each parameter combination. The red lines indicate which exploration tendency leads to the best decisions (i.e., the choice of options with the highest objective fit), depending on the accuracy. In figure **b**, the colours and contour lines indicate the number of time steps that have passed before the decision is made. In figure **c**, they indicate the average number of time steps options are explored in depth. The graphs show averages over 25,000 replicate simulation runs for each parameter combination.

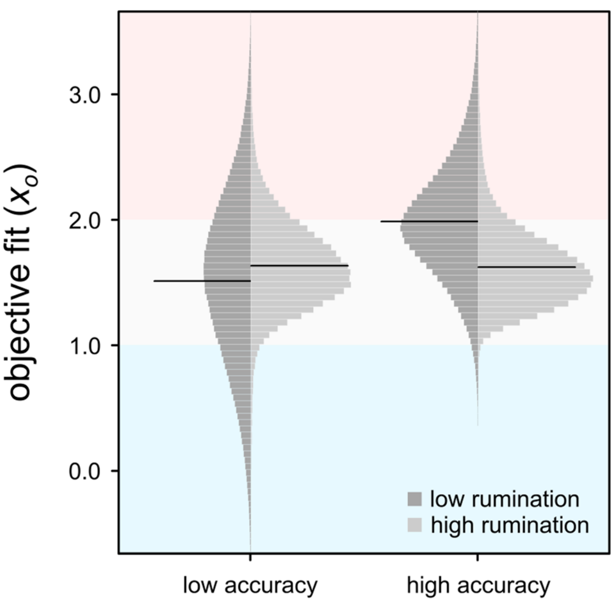

Fig. 4 Vertical histograms showing the distribution of the objective fit (x_o) of career choices, for low accuracy ($\alpha = 0.0$) and high accuracy ($\alpha = 0.5$). For both levels of accuracy, separate histograms are shown for simulation runs that had a low degree of rumination (where options were explored in-depth <10 times on average; in dark grey) and simulation runs that had a high degree of rumination (an average of at least 10 in-depth exploration events per option; in light grey). Black lines show the average objective fit associated with each histogram. The red-shaded area shows the region that is above the decision threshold ($\theta_2 = 2.0$); the blue-shaded area shows the region that is below the consideration threshold ($\theta_1 = 1.0$). All histograms are based on an exploration tendency of $m = 0.1$ (i.e., a tendency to explore mainly in depth). The graph is based on 1,000,000 replicate simulation runs for both values of accuracy.

choices for options that these individuals should in principle not even be willing to consider). The fraction of such very bad decisions is much reduced if these individuals ruminate more (compare the pair of leftmost histograms in Fig. 4).

Discussion

In sum, although the outcomes of our model often depend on the parameters in complex ways, a number of general patterns emerge from our model. Our model predicts that the best decisions are generally made by individuals who are highly accurate in evaluating how well an option will fit them, who have high standards for making their final decision, and who tend to broadly explore many options to acquaint themselves with possible alternatives. Additionally, rash decision making and rumination tend to have negative effects on the quality of the decision that is made. Having said that, our model also predicts that individual characteristics (exploration tendency, accuracy and selectiveness) and choice process characteristics (rash decision making and rumination) rarely have a straightforward impact on the quality of major life decisions, and that their effects are sometimes counter-intuitive. This shows the value of simulation approaches in producing consistent formulations of theory and generating testable hypotheses that one would not have arrived at by verbal reasoning alone.

Our study provides a concrete demonstration of how a formal modelling approach can clarify assumptions and definitions that were previously implicit or unclear. This is especially important when integrating distinct research traditions (in our case, decision science and identity theory): a formal modelling approach requires that concepts from different (sub)disciplines are placed in a single framework, thus forcing a substantive conceptual integration. For example, ruminative exploration is a concept from identity science that did not yet have a clear counterpart within decision science. Our formal modelling approach forced us to include this concept in our process-oriented decision-making framework in an explicit way. This led us to conceptualise ruminative exploration as an emergent outcome of the choice process (where individuals repeatedly explore the same option), rather than a priori assuming it to be a distinct type of exploration (as it is usually considered in identity science; see e.g. Luyckx et al., 2008).

Our formal modelling approach has not only been instrumental in integrating elements from distinct research traditions; it has also forced us to closely scrutinise some concepts from identity theory, leading to some clarifying insights. For example, identity theorists typically consider commitment and exploration to be distinct processes, but explicitly formalising decision making as a dynamic process has compelled us to re-evaluate that notion. In our model, commitment emerges as a result of the fit of an option on the one hand, and the selectiveness on the other. A certain level of commitment to an option is necessary in order to drive an individual to explore it in depth: only if the option seems fitting enough (given individual's standards), the individual will explore it again. This provides an interesting micro-process-level explanation for the finding that in-depth exploration is often correlated with both making a commitment and identifying with it (Luyckx et al., 2006), and suggests that exploration and commitment are much more intimately intertwined than commonly assumed. Similarly, our assumption that individuals cannot explore options indefinitely implies that they have to decide how much of their time they invest in broad exploration vs. in-depth exploration. Our simulation results show that this balance between both types of exploration is not trivial—it has considerable implications for the outcome of the choice process. However, this trade-off has not yet received attention in empirical studies on identity exploration. We do not claim that our views on these processes of exploration and commitment are necessarily better than others, but our approach does take a step closer to making definitions more explicit and coherent.

Our simulation model has generated a number of novel hypotheses that can be tested empirically. For example, our results shed light on the potential costs associated with 'maladaptive' features of major life decision making, such as ruminative exploration and rash decision making, which have thus far remained elusive (Dietrich et al., 2012). We predict that these features are in most cases damaging to the quality of the choice that is made, but that they can be beneficial in some cases. For individuals who are inaccurate in assessing how well options fit with their existing capabilities and preferences, we predict that ruminative exploration reduces the risk of making very bad decisions. For individuals who are not too selective, we predict that rash decision making is an efficient way to make a fast and satisfactory choice. Person centred empirical studies can be designed to test these predictions.

If the hypotheses generated by our model turn out to be empirically supported, they may eventually be helpful to inform practice. Our model has two distinct advantages in this regard. First, it is explicitly formulated on the individual level, which is the level that practitioners operate on. This means that empirical insights based on the hypotheses derived from our model have the potential to aid counsellors in tailoring their choice support strategies to the individual characteristics of their client. For example, our simulation results suggest that individuals who are not very sure about what they like or are good at may reach better decisions if they are stimulated to explore a few options in depth, rather than to explore many options broadly. This may be particularly helpful for the guidance of adolescents who have to make important education decisions, since adolescents tend to have lower self-concept clarity than adults (Crocetti et al., 2016). Second, our model explicitly integrates two elements that are both likely to be important in shaping counselling strategies around major life decisions: shorter-term mechanisms of decision making and longer-term patterns of identity development. For example, as we described above, counsellors may recommend a type of long-term exploration strategy that is suitable to that individual, but they may also attempt to improve micro-level dynamics, such as helping the individual estimate the fit of an option more accurately. Of course, such practical applications are still far off; the hypotheses generated by our model first have to be tested.

As any model, our model has not included all parameters that may affect the phenomenon of interest. In this study, we have chosen to limit ourselves to three factors (exploration tendency, accuracy and selectiveness), which are considered to be of proximal influence on the three key characteristics of the process of major life decision making, and which studies on identity development have revealed to differ considerably between individuals. However, this does not mean that we consider the influence of other factors to be unimportant. For example, a high degree of social support can perhaps enhance the accuracy with which individuals estimate the fit of options. Extensions of the model that include other factors may be valuable, provided that they do not complicate the model to such an extent that the results become uninterpretable. In similar vein, we chose to investigate the effect of some parameters by varying them across many different levels (exploration tendency, consistency), whereas we only considered a few levels of other parameters (both selectiveness thresholds), and held other factors entirely constant (e.g. the time allotted to make the final decision [100 time steps], the maximum number of options individuals could have under consideration simultaneously [three], and the relative weight of past experiences). We did not hold these values constant because we think they will not significantly affect the process of major life decision making—we simply chose to focus our study on the effects of factors that are of immediate influence on the three key characteristics of identity development processes. Depending on the question at hand (or simply to further explore model behaviour), it may be interesting to run simulations in which some other parameters are varied, or in which the same parameters are varied over a different range of values.

In our model, we make the implicit assumption that individuals assess the fit of options by comparing them to some kind of constant picture of their own interests and capabilities. In reality, it is likely that exploration also drives identity development by allowing individuals to learn about their own interests and capabilities, potentially leading them to become more accurate in the interpretations of the experiences that they have. One promising direction to extend our model is to explicitly incorporate this development in the exploration process—this would be particularly fitting for approximating decision-making processes that span long time periods (months or years). This could be done by allowing accuracy to improve over time, potentially in reaction to the options that individuals have explored.

Similarly, our implementation of 'objective fit' as a unidimensional, constant number that is drawn from a normal distribution is a choice that is convenient for modelling purposes. It reflects the assumption that the fit between individual and a major life decision is indicative for the quality of the decision, and that this fit is relatively constant on the short term. However, in reality, it is likely that the quality of a decision depends on more than a single fit-factor and that the fit of an option can change over time, both because of various types of changes in the individual (such as identity development) and with changes in the option. Other, more refined assumptions on this are conceivable, and may be worth exploring. Also, depending on the type of major life decision that is being made, the properties of the pool of possible options might differ in various regards, such as the number of options that are available and the degree to which the suitability of options differs. Of course, our assumption of an infinite pool of options with normally distributed objective fit is highly artificial, and it might affect the predicted outcome of the decision-making process. In any future efforts in modelling a specific type of major life decision making, this would be one of the more obvious opportunities to include more realism. Finally, we have assumed that the way individuals perceive the fit of options is absolute (i.e., it only depends on that option itself). However, there are reasons to suppose that individuals perceive the fit of an option as relative, dependent on the fit of other options they are considering (Stewart et al., 2006). Empirical work can help us to gain more insight in how individuals perceive the fit of options, and can serve to refine our model.

In our model, we have implemented a clear-cut divide between exploring an option and deciding on an option. This may be a more realistic assumption for some decisions than for others. For example, in the case of career choice this may be relatively realistic because there is a clear moment where the exploration phase ends and a decision is implemented by accepting a job or starting an educational trajectory. For other decisions this may be less realistic, such as in partner choice, where the transition from exploring an option to deciding on that partner may be more vague. However, also in this case, multiple decision moments are present: for example, an individual may choose a certain way to define the relationship when talking about it to others, or may choose to cohabit with and/or marry the partner.

Major life decisions result from a complex and dynamic choice process. The explicitly dynamic framework that we have introduced can help develop theory on how this process unfolds, and can serve to generate hypotheses that can be empirically tested. A number of predictions can be derived from the concrete model implementation that we have presented, including on how we should expect individual characteristics (exploration tendency, accuracy and selectiveness) to affect decision quality, and on under what circumstances we should expect the 'maladaptive' phenomena of rash decision making and ruminative exploration to emerge and when these are actually beneficial to the quality of the choices that are made. More generally, our model should be considered as a first step in a new direction of formally derived hypotheses, empirical tests of these hypotheses, and subsequent improvement of model assumptions. This approach has the potential to lead us to a better understanding of how these important decision-making processes work, and to eventually allow the design of individually tailored strategies to help individuals navigate these challenging major life decisions.

Data availability

The C++ code of the simulation model is publicly available on https://github.com/pvdberg1/major_life_decisions. This simulation model generates the data that was analysed in this paper. All R-scripts that produce the graphs are available on request.

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Author contributions

MAEvdG and PvdB designed research. PvdB ran simulations. MAEvdG and PvdB analysed the data and wrote the manuscript. ESK and PvG provided suggestions for improvement of the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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